

# Ocean Data Assimilation and Seasonal-Decadal Climate Prediction at GFDL

A.Rosati



# S/I Prediction Lessons

## 1. The initialization problem is different from the state estimation problem

- The best analysis may not be the best initialization
- Overspecification as in the close fit to the ocean data can introduce a lot of noise. Balance constraints between variables
- Particularly for the decadal initialization there may be an argument not to correct the mean state - but perhaps only correct the slowly varying component of the system eg. Large scale water mass properties
- Spurious inter-annual variability due to non-stationary nature of observing system

# S/I Prediction Lessons

## 2. Need good coupled models to assess the quality of initial conditions

- **Model errors rather than initial errors dominate SF performance**
- **For teleconnections, circulation changes, the performance of the model is even more critical**
- **Improvements in coupled models also translate on the ability of using SF as evaluation of ocean initial conditions.**

# S/I Prediction Lessons

## 3. Initializing from the assimilation analysis

- To the extent that things are linear, the climatology of the forecasts may be subtracted thus removing the drift. ***Can this method be used for decadal predictions?***
- Non-linearities could hurt- but starting close to reality lessens the problem.
- With the current generation of ocean data assimilation systems and coupled models it is possible to demonstrate the benefits of assimilating ocean data for the seasonal forecast skill

# ODA Research

**3D-variational method** – used in operational S/I prediction for over a decade. A minimum variance estimate using a constant prior covariance matrix, unchanged in time. Stationary filter.

**4D-variational**-A minimum variance estimate by minimizing a distance between model trajectory and observations using an adjoint to derive the gradient under model's constraint. Linear filter. (ECCO, JPL, Harvard)

**Ensemble filtering** – accounts for the nonlinear time evolution of covariance matrix. Low maintenance. Ensembles are efficient way to scale parallelism.

# Better Balanced Initialization

## Coupled Data Assimilation

“Assimilation of ocean data with a coupled model”

Coupled 4D-var: JAMSTEC

EnKF: GMAO, GFDL

## Coupled Breeding Vectors and Stochastic Optimals:

generation of the ensemble by projecting the uncertainty of the initial conditions on the fastest error-growth modes of the coupled system

## Anomaly Initialization:

Depresys (Met Office)

GECCO



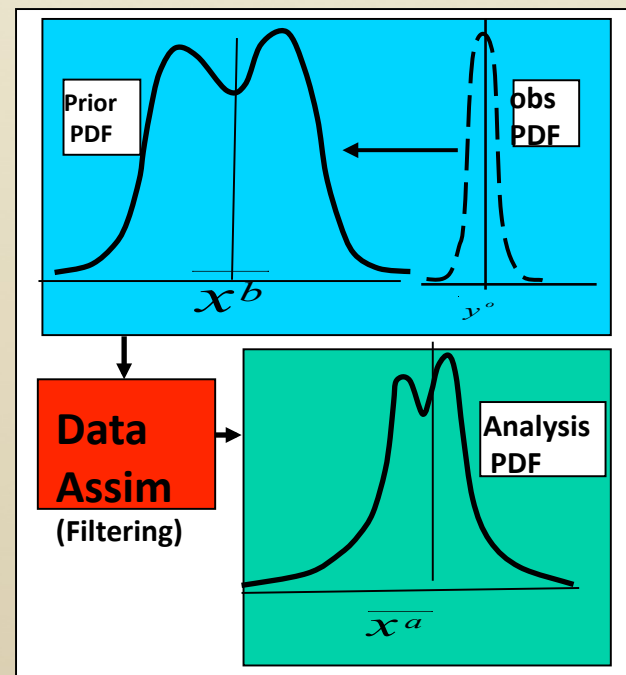
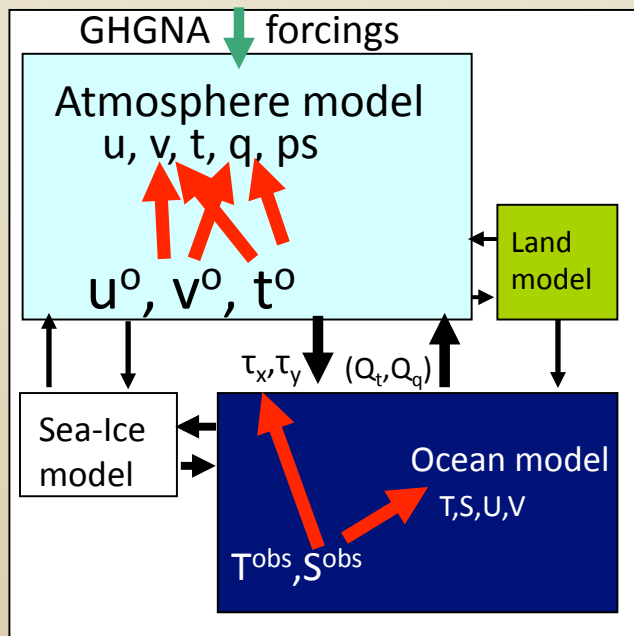
## **Ensemble Coupled Data Assimilation (ECDA) is at the core of GFDL prediction efforts**

- **Provides initial conditions for Seasonal-Decadal Prediction**
- **Provides validation for predictions and model development**
- **Ocean Analysis kept current and available on GFDL website**
- **Active participation in CLIVAR/GSOP intercomparisons**

# Pioneering development of coupled data assimilation system

Ensemble Coupled Data Assimilation estimates the **temporally-evolving probability distribution** of climate states under observational data constraint:

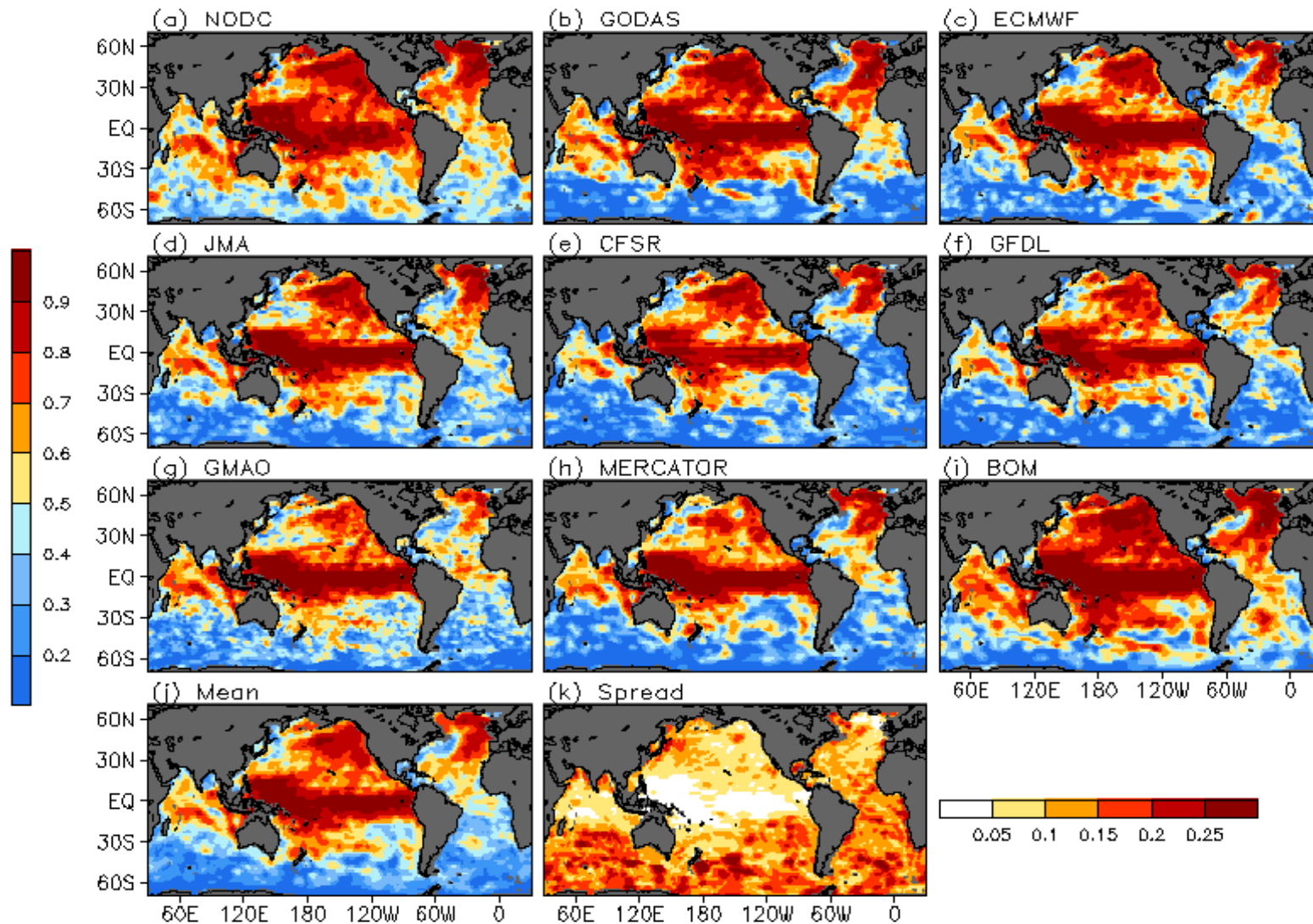
- Multi-variate analysis maintains physical balances between state variables such as T-S relationship – primarily geostrophic balance
- Ensemble filter maintains the nonlinearity of climate evolution
- All coupled components adjusted by observed data through instantaneously-exchanged fluxes
- Optimal ensemble initialization of coupled model with minimum initialization shocks



S. Zhang, M. J. Harrison,  
A. Rosati, and A.  
Wittenberg  
MWR 2007

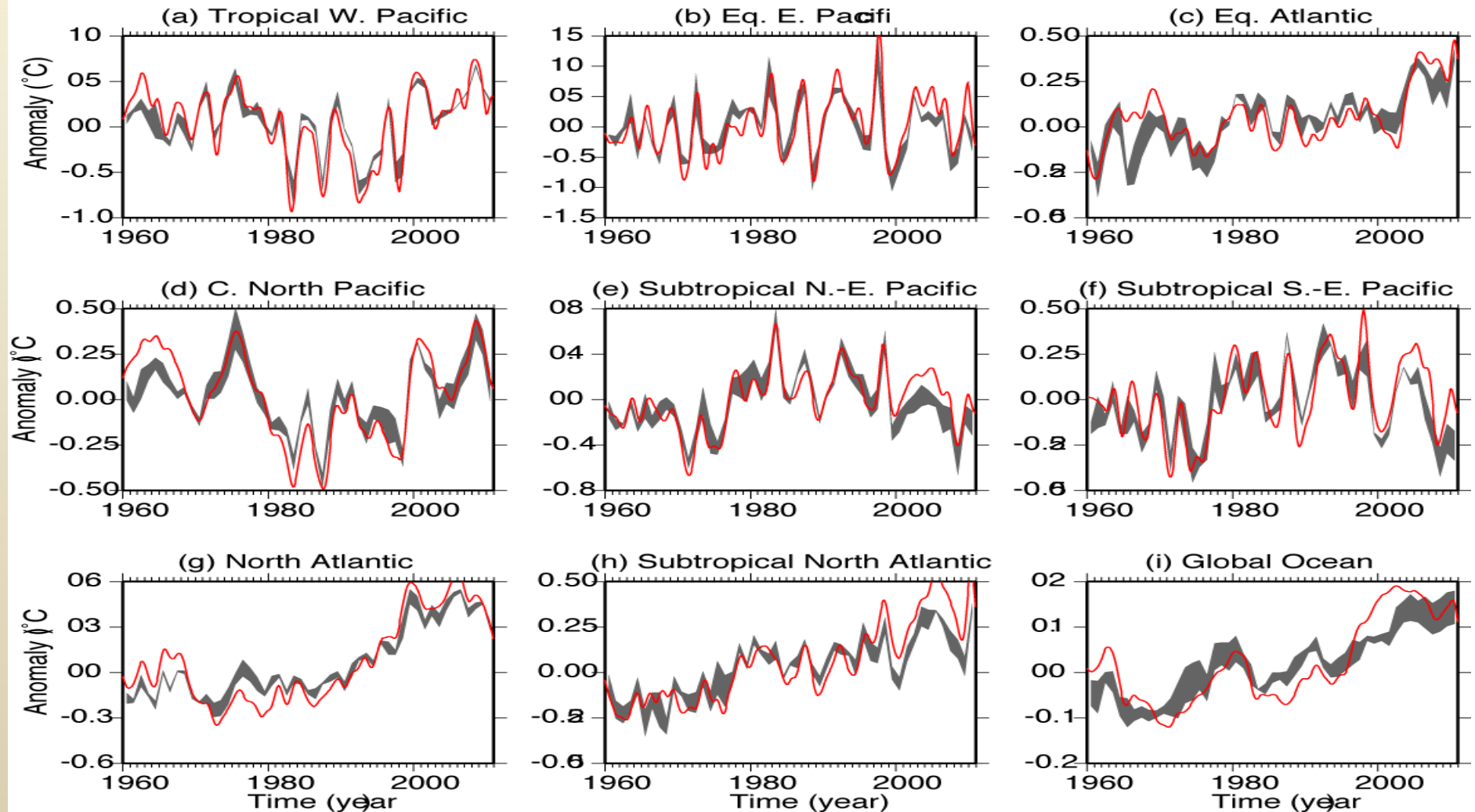


# Tav300 Anomaly Correlation with EN3



# Tav300 - (shading WOA, EN3); ECDA-red

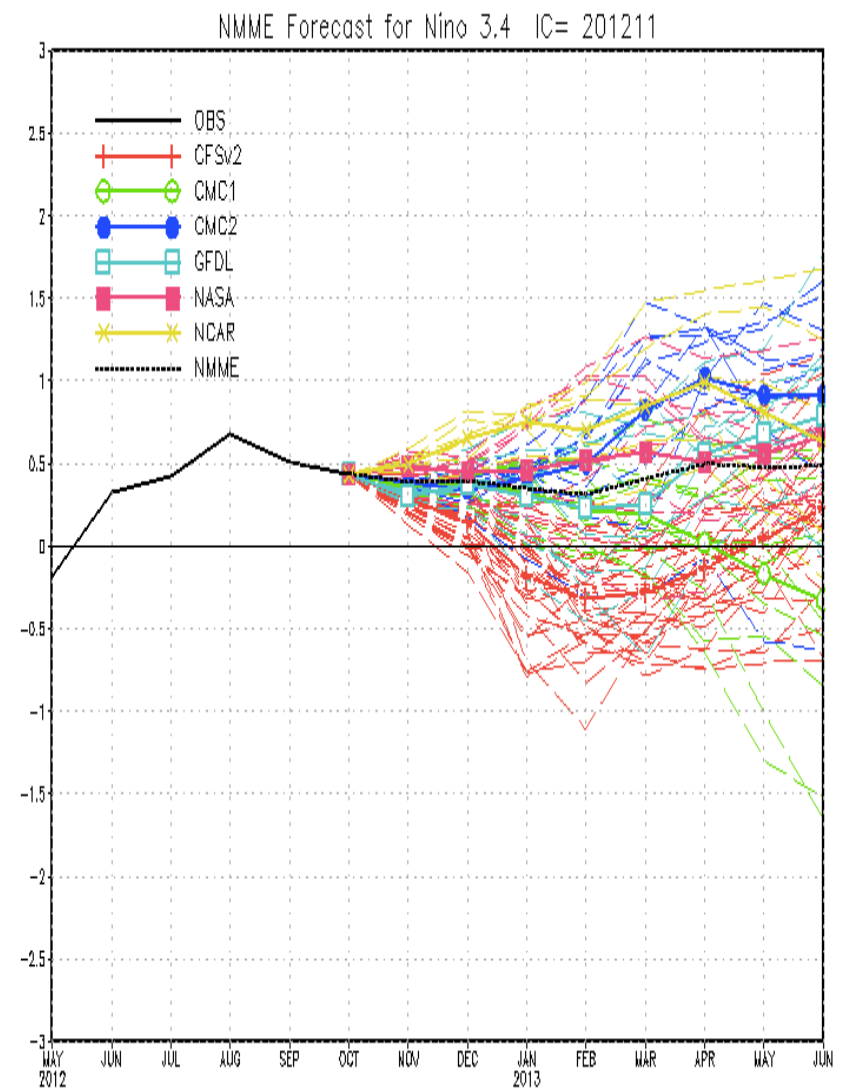
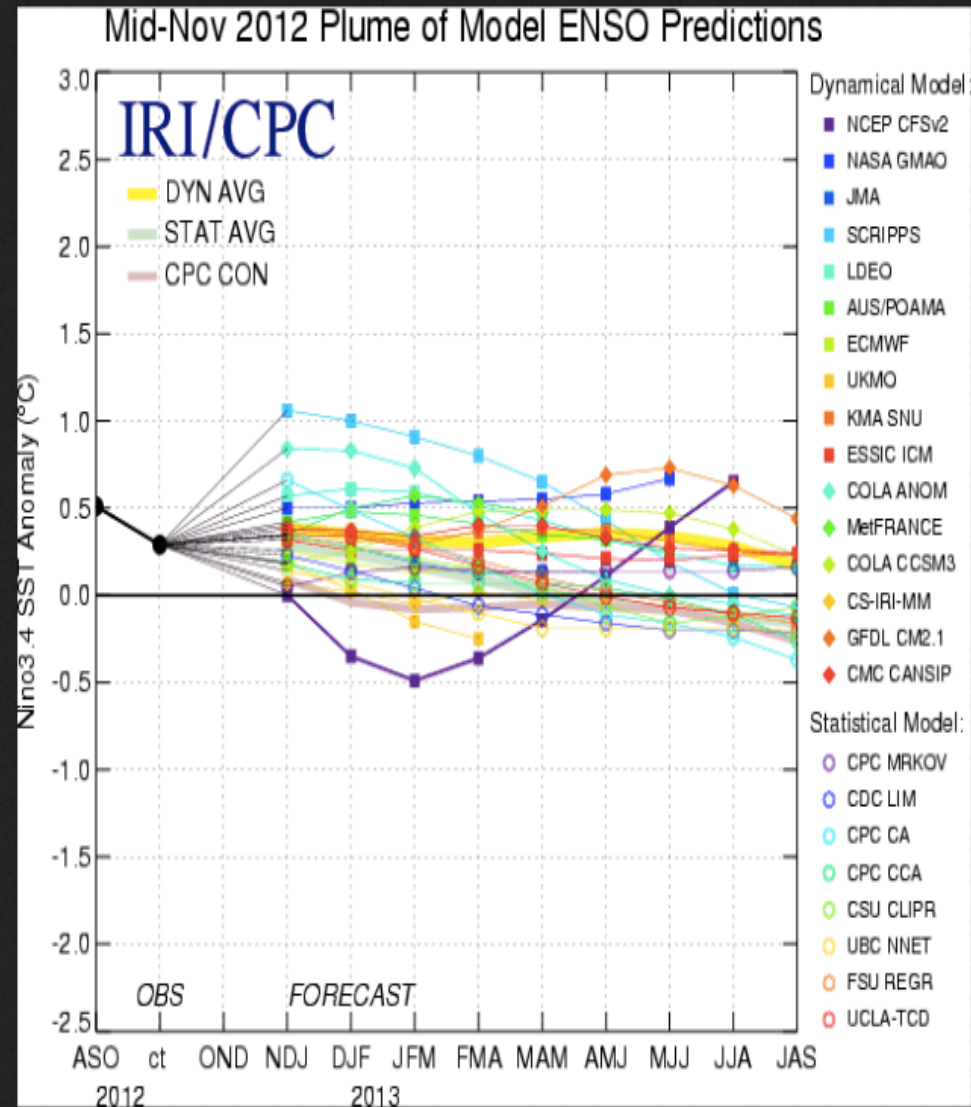
HC300 Anomaly (Shading=observation range; Red=ECDA)



## **ECDA research activities to improve Initialization**

- **Multi-model ECDA to help mitigate bias**
- **Fully coupled model parameter estimation within ECDA**
- **ECDA in high resolution CGCM**
- **Assess additional predictability from full depth ARGO profilers**

# Seasonal / Interannual Predictions - NMME



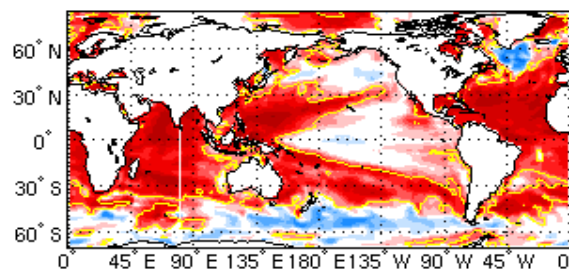


# DECADAL PREDICTION EXPERIMENTAL DESIGN

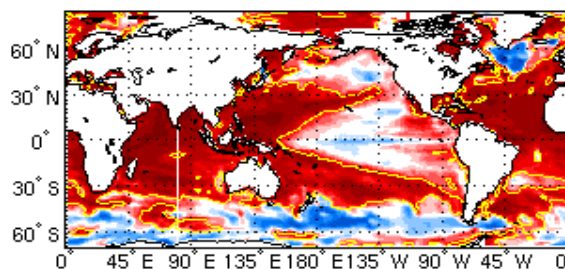
- Initialization- from Ensemble Coupled Data Assimilation (ECDA) Reanalysis
  - Atmosphere - NCEP Reanalysis2 (T,u,v,ps)
  - Ocean - xbt,mbt,ctd,sst,ssh,ARGO
  - Radiative Forcing - GHG, Solar, Volcano, Aerosol
- Hindcasts - 10 member ensembles, starting Jan every year from 1960-2012 for 10 years (total of >5k years)
- Predictions - RCP4.5 scenario
- Historic (uninitialized)- 10 member ensembles, 1860-2040, RCP4.5
- CM2.1 coupled model used for all experiments

# SST - ACC

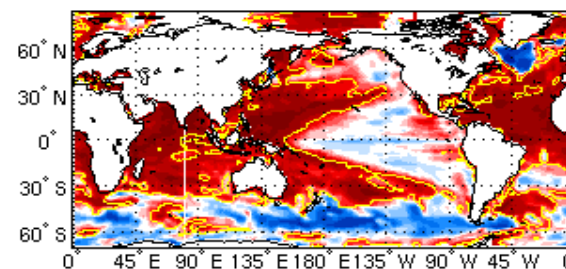
GFDL Year 1 (Obs= GFDL SST)  
ACC:Uninitialized Hindcast



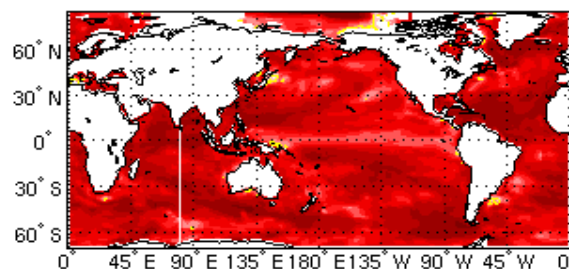
GFDL Year 2-5 (Obs= GFDL SST)  
ACC:Uninitialized Hindcast



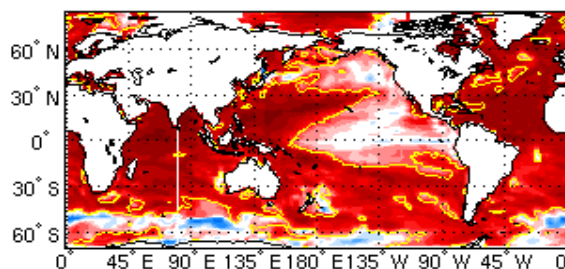
GFDL Year 6-10 (Obs= GFDL SST)  
ACC:Uninitialized Hindcast



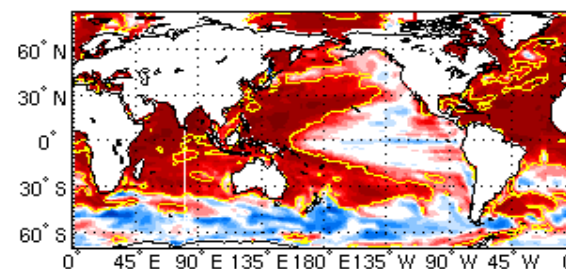
ACC:Initialized Hindcasts



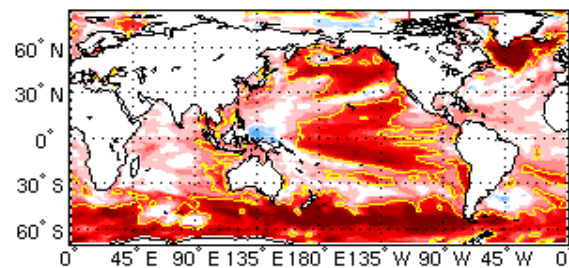
ACC:Initialized Hindcasts



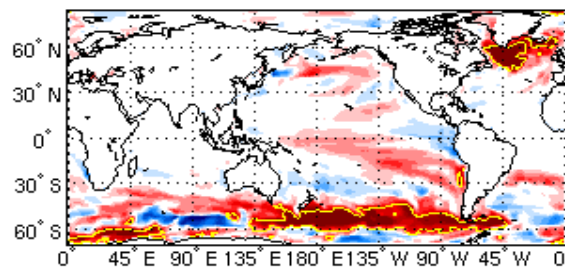
ACC:Initialized Hindcasts



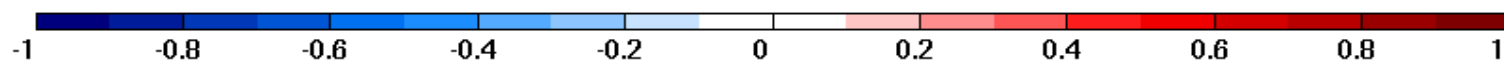
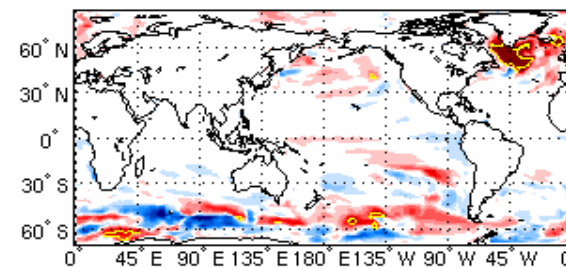
Diff. Initialized - Uninitialized



Diff. Initialized - Uninitialized

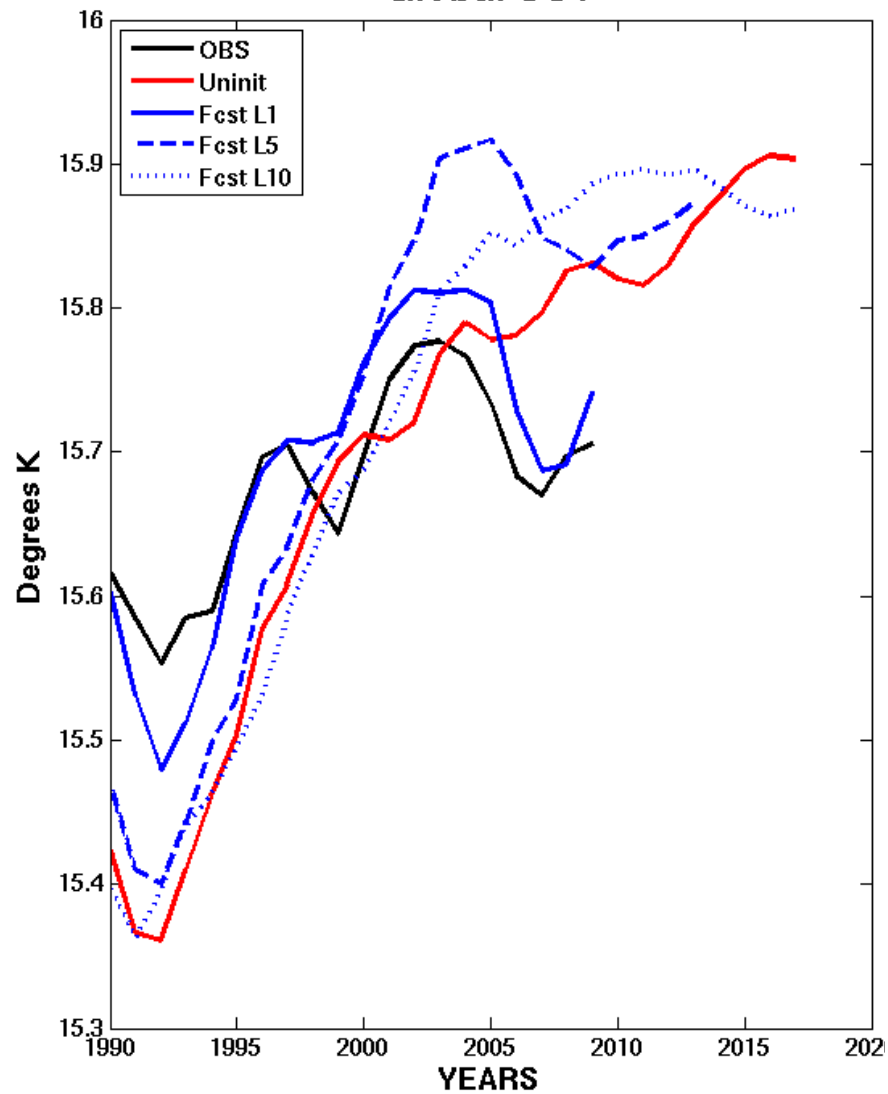


Diff. Initialized - Uninitialized

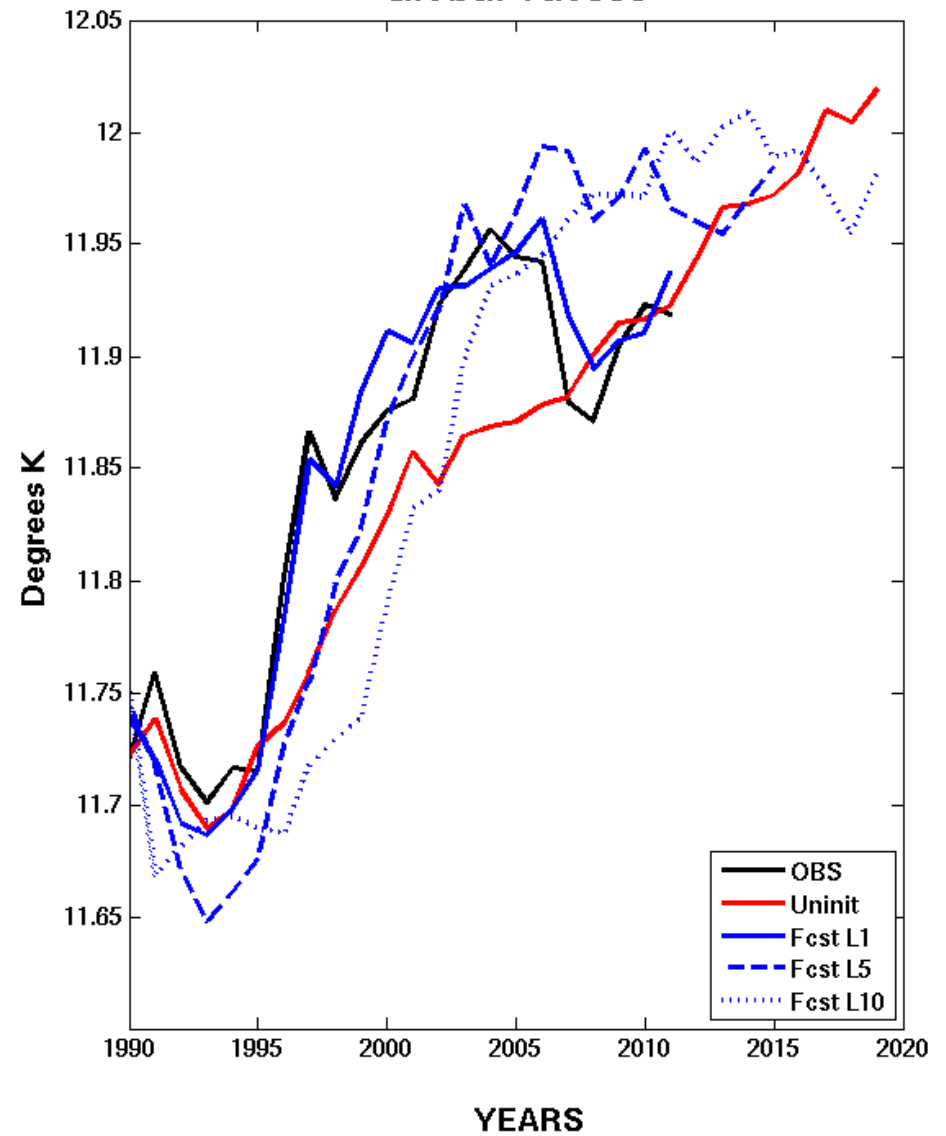




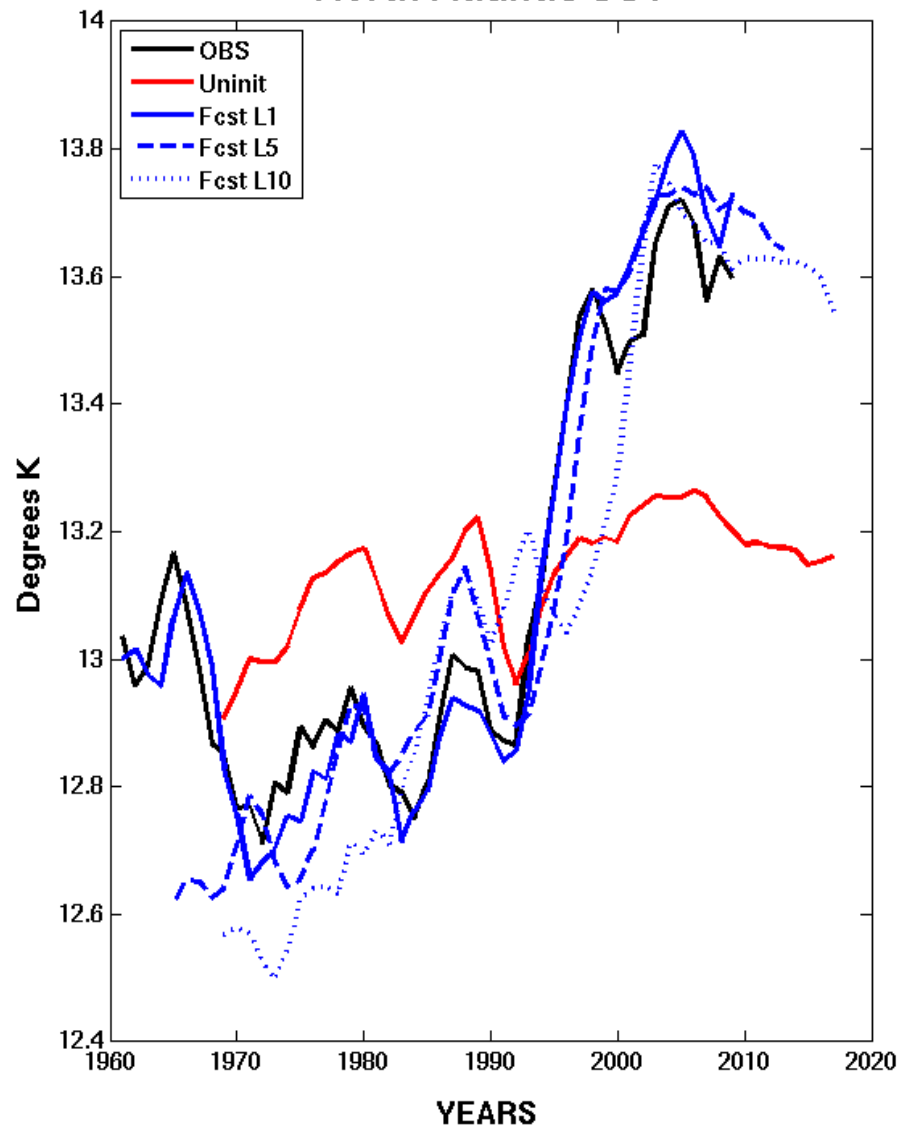
### Global SST



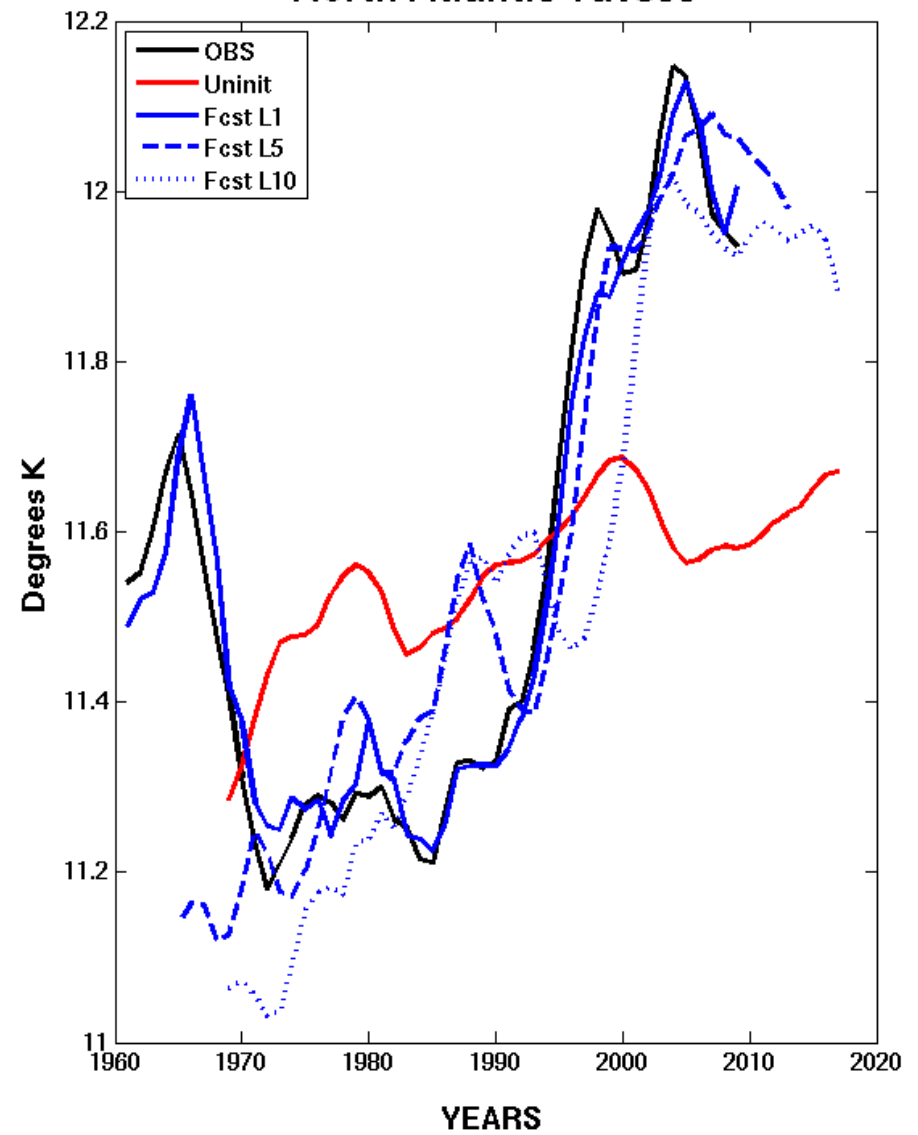
### Global Tav300



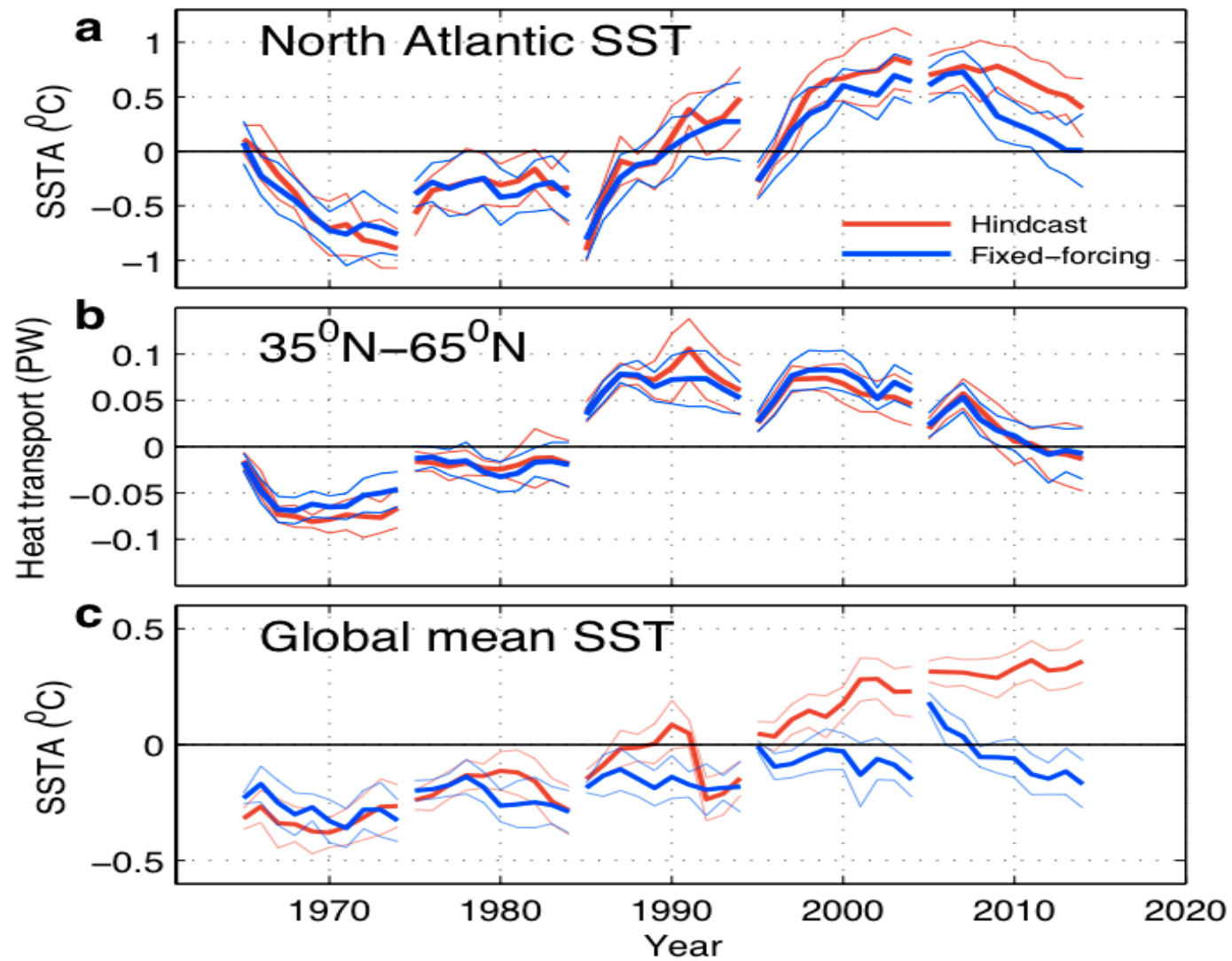
North Atlantic SST



North Atlantic Tav300



# NA SPG SST



# Summary

1. A series of initialized decadal hindcasts and forecasts as well as uninitialized historical runs were made in support of CMIP5 and IPCC AR5
2. Most of the decadal predictability is realized by the response to external radiative forcing
3. The initialization enhances prediction skill for internal decadal variability in the region of the AMO

# Caveats

1. Shortness of observational record leads to sampling uncertainty
2. Inhomogeneity of climate observing systems-quality of initial states
3. Climate not stationary - natural and anthropogenic radiative forcings
4. Predictability may be state dependent
5. Expectations are quite high and likely over-optimistic